Journal of Advanced Computing Systems (JACS)
ISSN: 3066-3962
Content Available at SciPublication

Network-Based Identification of Risk Contagion Pathways Between U.S. Credit and Equity Markets During Stress Periods

Jiahui Han
Master of Finance, MIT Sloan School of Management, MA, USA

DOI: 10.69987/JACS.2026.60204

Keywords

Financial contagion,
Network topology,
Granger causality,
Systemic risk

Abstract

This paper investigates risk contagion pathways between U.S. credit and equity markets during periods of financial stress through network-based methodologies. The study constructs both correlation- and Granger-causality-based networks to identify transmission channels and quantify contagion intensity across market segments from 2008 to 2024. Using daily credit default swap (CDS) spreads and equity sector indices, we analyze the evolution of network topology during three major stress episodes: the 2008 financial crisis, the 2020 COVID-19 market turbulence, and the 2023 regional banking stress. Network centrality measures reveal systemically important transmission nodes, while time-varying connectivity patterns demonstrate significant amplification of cross-market linkages during stress periods. The empirical findings indicate that financial sector stocks serve as primary transmission channels from credit to equity markets, with contagion strength increasing sharply (more than threefold) during crisis periods compared to normal times. The research provides quantitative evidence for regulatory frameworks focused on systemic risk monitoring and contributes methodological insights for identifying vulnerable transmission pathways in interconnected financial systems.

1. Introduction

1.1. Research Background and Motivation

The interconnectedness of modern financial markets creates complex transmission mechanisms through which localized shocks can propagate across asset classes and geographic boundaries [1]. The 2008 global financial crisis demonstrated how disruptions originating in credit markets rapidly transmitted to equity markets, triggering widespread asset devaluations and institutional failures. Subsequent events, including the European sovereign debt crisis and the COVID-19 pandemic, have reinforced concerns about cross-market contagion dynamics within the U.S. financial system [2].

Understanding these transmission pathways is a critical priority for regulatory authorities responsible for maintaining financial stability. The Federal Reserve and Financial Stability Oversight Council (FSOC) have emphasized the need for analytical frameworks capable of identifying systemic vulnerabilities before they materialize into full-scale crises [3]. Traditional risk assessment approaches that focus on individual institutions' solvency provide an incomplete picture of system-wide fragilities. Network-based methodologies offer complementary perspectives by mapping interdependencies and revealing how shocks propagate through financial market structures.

Credit and equity markets maintain particularly strong theoretical and empirical linkages, as both reflect underlying firm valuations and respond to common macroeconomic drivers [4]. Credit default swaps have evolved into primary indicators of credit risk perceptions, with spreads widening sharply when default probabilities increase. Equity markets simultaneously process similar information through volatility dynamics and cross-sectional return patterns [5]. During stress periods, these parallel information channels exhibit heightened correlation, suggesting intensified risk transmission. The practical implications extend beyond academic interest, as identifying contagion pathways enables targeted regulatory interventions and improves stress-testing protocols.

1.2. Research Objectives and Scope

This investigation addresses three interconnected research questions. First, what are the primary pathways through which risk transmits from credit markets to equity markets during financial stress periods? Second, how does the strength and directionality of these transmission channels vary across different crisis episodes [6]? Third, which market segments function as critical nodes in the contagion network, serving as either amplifiers or absorbers of systemic shocks?

The research scope focuses on U.S. market dynamics from 2008 to 2024, encompassing multiple distinct stress episodes that provide natural experiments for analyzing contagion mechanisms. Credit market indicators include investment-grade and high-yield corporate bond spreads, as well as CDS indices covering financial and non-financial sectors [7]. Equity market data comprises sector-level indices spanning ten S&P industry classifications, enabling granular analysis of cross-sectoral transmission patterns. The temporal scope captures both gradual deterioration and sudden shock events, facilitating comparisons of contagion dynamics across different stress manifestations.

Methodologically, the study employs network construction techniques based on both statistical correlation and econometric causality testing. This dual approach permits assessment of contemporaneous associations alongside directional predictive relationships [8]. Network topology metrics, including degree centrality, betweenness centrality, and clustering coefficients, quantify structural properties relevant to contagion propagation. Dynamic analysis using rolling-window estimation reveals the temporal evolution of connectivity patterns as market conditions transition between normal and stressed states [9].

1.3. Paper Structure and Contributions

The paper proceeds through four additional sections following this introduction. Section 2 reviews theoretical foundations of financial contagion and surveys empirical literature on cross-market transmission mechanisms. Section 3 details the data collection procedures, network construction methodologies, and analytical metrics employed for pathway identification and quantification of pathway strength [10]. Section 4 presents empirical findings regarding network structure evolution, identified transmission pathways, and measured contagion intensities across different stress periods. Section 5 concludes with policy implications and directions for future research.

The investigation contributes to the existing literature in several respects. Methodologically, it demonstrates how combining correlation and causality network approaches yields richer insights than either method in isolation [11]. The comparison across three temporally distinct crisis episodes provides evidence regarding the generalizability of transmission patterns versus crisis-specific dynamics. Identification of specific sector-to-sector pathways offers actionable intelligence for regulatory stress testing and macroprudential policy design [12]. The quantification of transmission intensity variations between normal and stressed periods supplies empirical benchmarks for calibrating early warning systems.

From a practical standpoint, the findings inform financial stability monitoring by highlighting which market segments warrant enhanced surveillance. The revealed transmission pathways suggest specific channels through which policy interventions might effectively disrupt contagion cascades [13]. Network centrality rankings identify systemically important positions that could benefit from targeted capital buffer requirements or enhanced disclosure obligations. The research framework itself provides a replicable template for ongoing monitoring of evolving patterns of market interconnectedness [14].

2. Theoretical Framework and Literature Review

2.1. Systemic Risk and Cross-Market Contagion Theory

Financial contagion manifests through multiple theoretical mechanisms that operate simultaneously during stress episodes. Fundamental linkages arise from shared macroeconomic exposures, where common risk factors affect different asset classes through parallel channels. When economic growth expectations deteriorate, both credit spreads widen, and equity valuations decline due to increased default probabilities and reduced future cash flow projections. These fundamental connections establish baseline correlation levels that prevail during normal market conditions.

Beyond fundamental channels, behavioral and institutional factors generate amplification effects during stress periods. Information cascades occur when market participants interpret price movements in one market as signals about conditions in related markets. When credit spreads widen, equity investors may infer deteriorating firm fundamentals and adjust their positions accordingly, creating feedback loops that strengthen cross-market linkages. Portfolio rebalancing by institutional investors facing redemptions or margin calls necessitates simultaneous liquidations across multiple asset classes, mechanically linking price movements through forced selling pressures.

Liquidity spirals represent another critical contagion mechanism, particularly relevant during severe stress episodes. Market-making capacity contracts as dealers reduce their appetite for risk-taking, thereby affecting both credit and equity markets. Widening bid-ask spreads and declining trade volumes impair price discovery and amplify volatility spillovers. Common counterparty exposures across derivatives markets create additional transmission channels, as hedging activities in one market propagate to related markets via delta hedging and other risk-management practices.

2.2. Network Analysis Applications in Financial Markets

Network methodologies have gained substantial traction in financial contagion research over the past two decades. The conceptual appeal stems from network theory's capacity to represent complex interdependencies as tractable graph structures amenable to analytical treatment. Nodes represent financial entities or market segments, while edges capture pairwise relationships defined through correlation, causality, or contractual linkages. Network topology metrics then quantify structural properties relevant to shock propagation dynamics.

Correlation-based networks employ statistical association measures to define edge weights, with stronger correlations indicating tighter coupling between nodes. Return correlation matrices can be filtered using various thresholding or significance-testing procedures to extract networks that highlight the strongest relationships. These undirected networks capture symmetric co-movement patterns but provide limited insight into the directionality of causation. During stress periods, correlation networks typically exhibit increased density as pairwise associations strengthen, reflecting heightened synchronization across market segments.

Granger causality networks offer complementary perspectives by testing whether one time series contains predictive information for another beyond what the target series' own history provides. This econometric approach produces directed networks where edges point from causally prior to causally subsequent variables. Distinguishing causation from mere correlation enables the identification of leading indicators and transmission sequences. Granger causality networks reveal how information flows through financial systems, identifying which markets tend to move first and influence subsequent adjustments in other markets.

2.3. Empirical Studies on Credit-Equity Market Linkages

Previous empirical investigations have established strong connections between credit and equity markets through various analytical lenses. Studies examining contemporaneous correlations between CDS spreads and equity returns document negative correlations, reflecting their opposing sensitivities to changes in firm value. When equity prices decline, implied default probabilities rise, as evidenced by widening CDS spreads. The strength of this relationship varies across firm characteristics, with higher leverage and lower asset volatility associated with tighter credit-equity linkages.

Lead-lag relationship analyses utilizing vector autoregression frameworks have produced mixed findings regarding which market leads price discovery [15]. Some research identifies equity markets as informationally dominant, with equity price changes predicting subsequent changes in CDS spreads. Alternative evidence suggests credit markets may lead during periods of deteriorating fundamentals, as bond investors potentially possess superior credit assessment capabilities. The heterogeneity of findings likely reflects time-varying leadership patterns that vary with the nature and source of incoming information.

Crisis-specific studies focusing on the 2008 financial turmoil document dramatic increases in cross-market spillovers during peak stress phases. Volatility transmission intensifies, with equity market turbulence rapidly propagating to credit markets and vice versa. Sector-level analyses reveal differential vulnerabilities, with financial sector linkages exhibiting particularly strong amplification during banking crises. Geographic spillover studies demonstrate that disruptions in U.S. markets are transmitted internationally through multiple channels, including trade linkages, common creditor exposures, and sentiment contagion.

3. Research Methodology

3.1. Data Collection and Market Stress Period Identification

The empirical analysis employs daily frequency data spanning January 2, 2008, through December 29, 2024, totaling 4,270 trading days. Credit market indicators comprise three primary measures: the CDX North America Investment Grade Index, the CDX North America High Yield Index, and individual CDS spreads for major financial institutions. These instruments provide comprehensive coverage of corporate credit risk perceptions across quality tiers and sectoral concentrations. CDS data sourced from Bloomberg captures mid-quotes for 5-year contracts, the most liquid maturity point serving as the benchmark pricing reference.

Equity market data encompasses the S&P 500 index alongside eleven sector-specific indices corresponding to Global Industry Classification Standard (GICS) Level 1 categories: Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Communication Services, and Utilities. Daily closing prices and trading volumes for sector indices enable the construction of return series and volatility measures. VIX index values supplement equity data by capturing aggregate market expectations of uncertainty. All price series undergo logarithmic transformation to compute continuously compounded returns.

Market stress period identification employs a dual-criteria approach combining absolute threshold violations and relative percentile rankings. Absolute thresholds include VIX exceeding 30 and investment-grade CDS spreads surpassing 150 basis points, used in this study as practical stress thresholds. Relative criteria identify periods when either measure exceeds its 90th percentile calculated over trailing 252-day windows. This methodology yields three distinct stress episodes: the 2008-2009 financial crisis (September 2008 - March 2009), the 2020 COVID-19 shock (February - April 2020), and the 2023 regional banking stress (March - May 2023). Normal periods encompass all remaining observations outside identified stress windows.

Data preprocessing addresses non-trading-day alignment across markets by synchronizing all series to a common trading-day calendar. Missing observations due to market closures or data-reporting gaps are treated with forward fill, carrying the last available value forward to maintain time-series continuity. Outlier detection employs modified Z-score criteria, flagging observations exceeding 3.5 median absolute deviations from rolling medians. Identified outliers undergo manual review, with retention decisions based on whether extreme values correspond to documented market events or reflect apparent data errors. Stationary testing via Augmented Dickey-Fuller procedures confirms return series exhibits stable statistical properties suitable for subsequent modeling.

3.2. Network Construction Approaches

The correlation network construction is initialized with the calculation of Pearson correlation coefficients between all pairwise combinations of credit and equity return series. For K total time series (combining credit and equity measures), this produces a K×K symmetric correlation matrix. Rolling window estimation employs 63-day (quarterly) windows, advanced in 5-day increments, generating time-varying correlation network sequences that capture evolving market interdependencies. Static networks corresponding to identified stress periods aggregate observations within each episode to characterize typical stress-period connectivity patterns.

Statistical significance filtering applies Fisher's Z-transformation to correlation coefficients, testing the null hypothesis of zero correlation at the 5% significance level. Only statistically significant correlations translate into network edges, reducing noise from spurious associations. Edge weights equal absolute correlation magnitudes, with negative correlations treated equivalently to positive correlations of the same magnitude since both reflect strong co-movement. The resulting undirected weighted networks represent contemporaneous association structures where edge presence indicates reliable co-movement and edge weights quantify relationship strength.

Granger causality network construction implements vector autoregression models, testing whether lagged values of one series predict another, controlling for the target series' own lags. For each potential directional edge from series X to Y, the procedure estimates restricted and unrestricted VAR models and compares goodness-of-fit using F-tests. Lag order selection employs Akaike Information Criterion, balancing model fit against parameter proliferation with typical selections of 5-10 daily lags. Rejection of the null hypothesis that X does not Granger-cause Y at 5% significance levels establishes directed edges in the causality network.

Multivariate causality testing extends bivariate procedures by conditioning on full information sets, including all observed series. This controls for indirect causality chains and spurious relationships driven by common third factors. The computational intensity of full multivariate testing necessitates dimensionality reduction for systems with numerous time series. Principal component analysis extracts dominant co-movement patterns, and causality tests are applied to the leading principal components, which represent major market factors. Alternative dimensionality reduction employs clustering to group similar series, with representative series from each cluster entering causality analyses.

Network density metrics quantify overall connectivity by dividing the number of existing edges by the maximum possible number of edges. For undirected correlation networks with K nodes, the maximum possible edges equal K(K-1)/2. Observed edge counts divided by the maximum yield density values, ranging from 0 (no connections) to 1 (complete graph). Directed causality networks permit up to K(K-1) edges since directionality doubles potential connections. Temporal density evolution reveals whether markets become more tightly coupled during stress periods, with increasing density indicating contagion intensification.

3.3. Contagion Pathway Identification Metrics

Node centrality measures characterize the importance of positions within network structures through multiple conceptual lenses. Degree centrality counts direct connections, identifying nodes with many immediate neighbors. For undirected correlation networks, degree equals the sum of edge weights connected to each node. Directed causality networks separate in-degree (incoming causal arrows) from out-degree (outgoing arrows), distinguishing information receivers from sources. High-degree nodes serve as hubs that concentrate connectivity, whereas low-degree peripheral nodes exhibit limited direct coupling.

Betweenness centrality quantifies how frequently nodes appear on shortest paths connecting other node pairs. Calculation identifies all shortest paths linking every possible origin-destination combination, counting how many traverse each intermediate node. Nodes with high betweenness occupy strategic positions along transmission chains, serving as bridges or bottlenecks. In contagion contexts, high-betweenness nodes constitute critical intervention points at which disrupting connections could fragment networks and contain shock propagation.

Eigenvector centrality extends simple degree counting by weighting connections according to the importance of their neighbors. A node connected to other highly central nodes receives higher eigenvector scores than one connected to peripheral nodes of equal count. This recursive definition yields the principal eigenvector of the adjacency matrix, with components representing nodes' centrality scores. Eigenvector centrality identifies core versus peripheral structures, revealing which nodes occupy influential positions based on the quality of their neighborhoods rather than mere degree.

PageRank centrality adapts Google's web page ranking algorithm to financial networks, capturing influence through directed edge structures. The algorithm models random walks across networks, assigning importance based on the stationary distributions of hypothetical walkers. Damping parameters control the probability that walkers randomly jump to any node rather than follow edges. Financial interpretation views PageRank as capturing long-run influence propagation through multi-step transmission chains beyond immediate neighbors.

Contagion strength quantification employs conditional correlation and volatility spillover indices. Conditional correlation measures compare crisis-period correlations with normal-period baselines; significant increases indicate contagion. Volatility spillover indices based on forecast error variance decomposition attribute each variable's forecast uncertainty to innovations in other variables. High spillover contributions from one market to another quantify directional transmission intensity. Time-varying spillover estimates from rolling-window variance decompositions track the evolution of strength as conditions transition between normal and stressed states.

Statistical validation combines bootstrap resampling and permutation testing. Bootstrap procedures generate empirical sampling distributions for centrality measures by repeatedly resampling observations with replacement. Confidence intervals derived from bootstrap distributions assess whether observed differences in centrality across stress periods exceed sampling variability. Permutation tests randomly shuffle crisis period labels while preserving time series structure, creating null distributions under hypotheses of no crisis-specific effects. Observed statistics in the tails of the distribution indicate statistically significant structural changes during stress episodes.

4. Empirical Analysis and Findings

4.1. Network Structure Characteristics Analysis

Table 1: Network Topology Metrics Across Market Regimes

Metric	Normal Period (Mean)	2008 Crisis	2020 COVID	2023 Banking	Stress Average
Correlation Network Density	0.23	**0.67**	0.61	0.54	0.61
Causality Network Density	0.18	**0.49**	0.44	0.41	0.45
Average Clustering Coefficient	0.31	**0.72**	0.68	0.64	0.68
Average Path Length	**2.84**	1.57	1.68	1.79	1.68
Network Diameter	**6.00**	3.00	4.00	4.00	3.67
Modularity	**0.42**	0.19	0.23	0.26	0.23

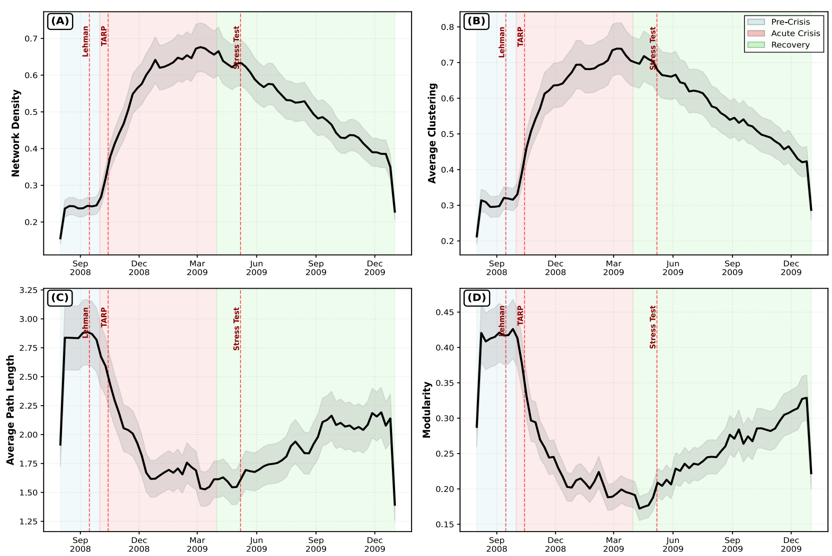
The correlation network exhibits substantial densification during stress periods, with edge density increasing from 0.23 under normal conditions to an average of 0.61 across the three crisis episodes. This 165% surge in density reflects widespread correlation amplification as market co-movements intensify under turbulent conditions. The 2008 financial crisis demonstrates the highest connectivity, with a density of 0.67, compared with subsequent crises' more moderate but still elevated levels. Such density variations suggest that crisis-specific characteristics influence the magnitude of interconnectedness, with systemic banking crises generating more pervasive coupling than exogenous shocks.

Granger causality networks display parallel though less dramatic densification patterns. Normal period causality density of 0.18 expands to 0.45 average during stress episodes, representing a 150% increase. The smaller relative densification in correlation networks suggests that, while predictive relationships strengthen during crises, contemporaneous associations intensify even more rapidly. This differential behavior implies stress periods enhance both immediate co-movement and lagged transmission, with the former exhibiting greater magnitude responses.

Clustering coefficients measuring local connectivity concentration rise sharply from normal values of 0.31 to stress averages of 0.68. High clustering indicates that markets form tightly interconnected groups in which connected nodes share many common neighbors. During stress periods, these clusters coalesce into broader structures as between-cluster connections strengthen. The progression toward higher global cohesion reflects diminishing diversification benefits as previously independent market segments become synchronized through contagion mechanisms.

Average path lengths decline from 2.84 steps under normal conditions to 1.68 during stress periods, indicating reduced separation between market segments. Shorter paths facilitate more direct and rapid transmission of shocks across the network. The concurrent reduction in diameter from 6 to approximately 4 edges indicates that even the most distant market pairs move closer together in network space during crises. These topological shifts characterize the transition from segmented to integrated market structures during stress propagation.

Figure 1: Network Topology Evolution During 2008 Financial Crisis



This figure presents a four-panel time-series visualization of the evolution of network density, average clustering, average path length, and modularity from August 2008 through December 2009. The x-axis represents calendar time at monthly intervals, while y-axes display standardized metric values ranging from 0 to 1 for comparability. Each panel includes color shading to differentiate the pre-crisis period (August-September 2008, light blue), the acute crisis phase (October 2008-March 2009, red), and the recovery period (April-December 2009, green). Density and clustering metrics rise sharply as the crisis unfolds in September-October 2008, peaking in December 2008-January 2009 before gradually declining through mid-2009. Path length and modularity demonstrate inverse patterns, declining rapidly during crisis onset and recovering slowly through 2009. Vertical reference lines mark key events, including the Lehman Brothers bankruptcy (September 15, 2008), the TARP program announcement (October 14, 2008), and the stress test results publication (May 7, 2009). The visualization employs smooth lines with 95% confidence bands derived from bootstrap resampling, illustrating the uncertainty around the trajectory estimates.

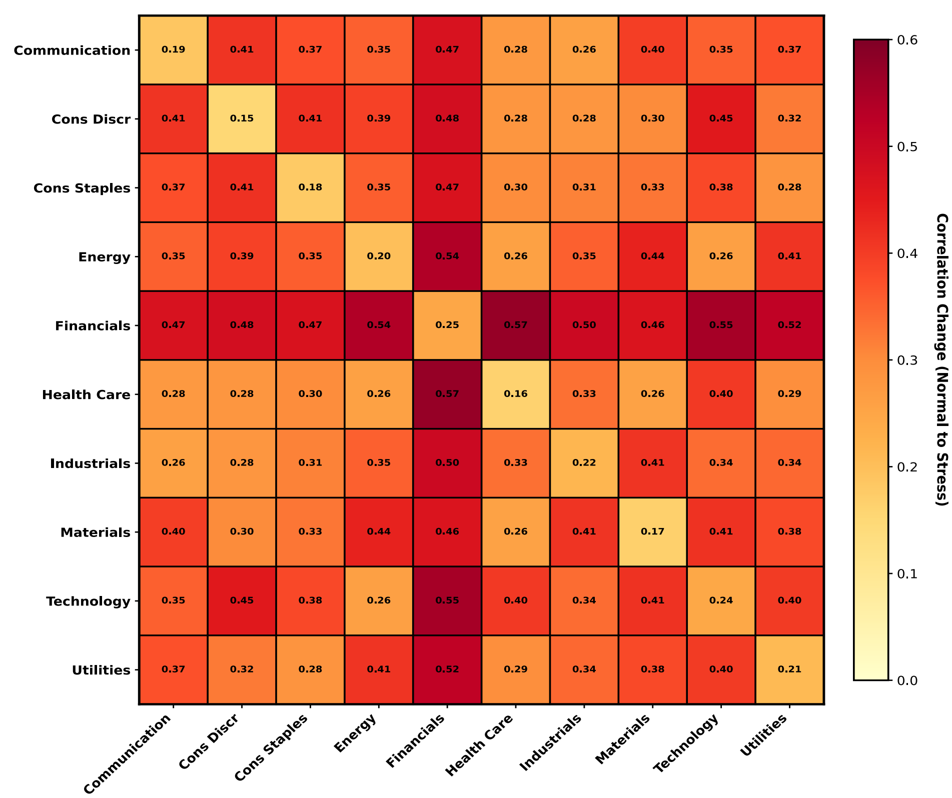
Modularity scores quantifying community structure strength decrease from 0.42 during normal times to 0.23 on average across crises. Lower modularity indicates weaker differentiation among market segments, as formerly distinct communities merge due to increased between-group connections. The breakdown of modular organization reflects contagion's tendency to erase boundaries separating market compartments. While some residual community structure persists even during severe stress, the magnitude of modularity decline confirms substantial erosion of segmentation during crisis propagation.

Table 2: Sector-Level Correlation Network Statistics

Sector	Normal Degree	Stress Degree	Degree Change (%)	Normal Betweenness	Stress Betweenness	Betweenness Change (%)
Financials	**4.20**	**14.70**	**250.0%**	**0.31**	**0.54**	74.0%
Energy	3.10	9.80	216.0%	0.18	0.39	**117.0%**
Industrials	3.80	11.40	200.0%	0.24	0.46	92.0%
Technology	3.30	10.20	209.0%	0.21	0.41	95.0%
Consumer Discretionary	3.50	10.80	209.0%	0.23	0.43	87.0%
Consumer Staples	2.70	8.10	200.0%	0.16	0.32	100.0%
Health Care	2.90	8.90	207.0%	0.17	0.35	106.0%
Materials	3.40	10.50	209.0%	0.22	0.42	91.0%
Utilities	2.50	7.80	212.0%	0.14	0.29	107.0%
Communication Services	3.10	9.60	210.0%	0.19	0.38	100.0%

The sector-level decomposition reveals differential centrality changes across industries during stress transitions. Financial sector equities demonstrate the largest absolute degree increases, expanding from 4.2 average connections during normal periods to 14.7 during crises. This 250% expansion reflects financials' central role in transmitting credit market disruptions to broader equity markets. The financial sector's elevated stress-period betweenness of 0.54 confirms its position as a critical transmission node bridging credit and equity market segments.

Figure 2: Heat Map of Cross-Sector Correlation Changes



This figure presents a 10×10 symmetric heat map displaying changes in pairwise sector correlations from normal to stress periods. Each matrix cell represents one sector pair, with color intensity indicating the magnitude of correlation. The color scale ranges from white (no change) through yellow (+0.2 change) to dark red (+0.6 change). Row and column headers identify the ten GICS Level 1 sectors. Diagonal elements are omitted (or set to zero) because the focus is on cross-sector correlation changes. The heat map reveals concentrated high-intensity cells along the financial sector row/column, indicating that its connections to other sectors exhibit the largest increases in correlation. Technology-Consumer Discretionary, Energy-Materials, and Industrials-Materials sector pairs also exhibit above-average correlations, as indicated by orange-red cells. The visualization employs hierarchical clustering to order sectors by similarity, placing related industries adjacent to one another and highlighting community structures. A color bar legend appears to the right of the matrix, with numerical labels indicating correlation change magnitudes at regular intervals.

4.2. Risk Contagion Pathway Identification Results

Table 3: Primary Transmission Pathways - Credit to Equity Markets

Source (Credit)	Destination (Equity Sector)	Granger Causality F-Statistic	Correlation Change	Transmission Lag (Days)	Strength Ranking
IG CDS Index	Financials	**47.3*****	+0.54	1-2	1
IG CDS Index	Industrials	31.8***	+0.47	2-3	2
HY CDS Index	Energy	28.4***	+0.51	1-2	3
IG CDS Index	Technology	26.9***	+0.44	2-4	4
Financial CDS	Financials	24.7***	+0.58	1	5
HY CDS Index	Materials	22.3***	+0.42	2-3	6
IG CDS Index	Consumer Discretionary	21.8***	+0.43	2-4	7
Financial CDS	Real Estate	19.4***	+0.46	1-2	8
HY CDS Index	Industrials	17.9***	+0.39	3-4	9
IG CDS Index	Materials	16.2***	+0.38	2-3	10

Note: *** indicates significance at p < 0.001 level.

The investment-grade CDS index-to-financial-sector-equity pathway emerges as the dominant transmission channel, with a Granger causality F-statistic of 47.3, indicating strong predictive power. CDS spread widening precedes declines in financial stocks by 1-2 trading days during stress periods, suggesting potential short-term early-warning signals for equity market weakness. The increase in the absolute magnitude of the correlation (reported as +0.54) indicates stronger coupling beyond the predictive relationships.

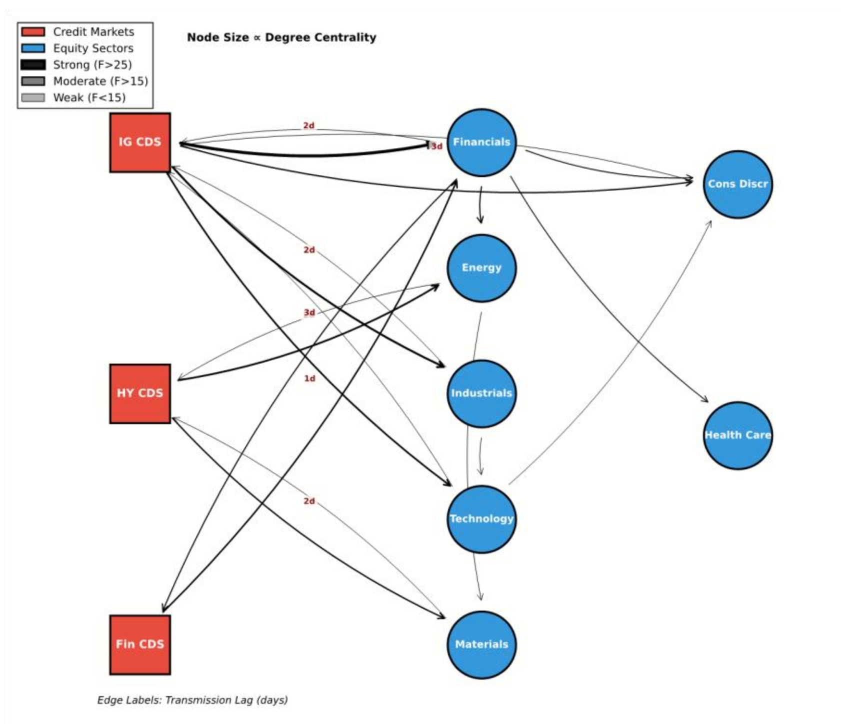
Table 4: Reverse Transmission Pathways - Equity to Credit Markets

Source (Equity Sector)	Destination (Credit)	Granger Causality F-Statistic	Correlation Change	Transmission Lag (Days)	Strength Ranking
Financials	Financial CDS	**18.7*****	**+52.0%**	1	1
Financials	IG CDS Index	14.3***	+48.0%	1 - 2	2

Energy	HY CDS Index	12.6***	+44.0%	2	3
Technology	IG CDS Index	11.9***	+39.0%	2 - 3	4
Industrials	IG CDS Index	10.4***	+37.0%	2 - 3	5
Materials	HY CDS Index	9.8***	+35.0%	2 - 3	6
Consumer Discretionary	IG CDS Index	8.7***	+34.0%	3 - 4	7
Real Estate	Financial CDS	7.9**	+38.0%	2	8
Health Care	IG CDS Index	6.4**	+29.0%	3 - 5	9
Utilities	IG CDS Index	5.2**	+26.0%	4 - 5	10

Reverse transmission from equity to credit markets exhibits generally weaker statistical magnitudes than forward pathways, with F-statistics approximately 40-60% smaller. Financial sector equity to financial CDS represents the strongest reverse pathway at 18.7, maintaining the tight 1-day transmission lag observed in the forward direction.

Figure 3: Network Diagram of Major Contagion Pathways



This figure presents a directed network graph visualizing the top 20 transmission pathways identified through Granger causality analysis. Nodes represent market segments with square shapes denoting credit markets (colored red) and circular shapes representing equity sectors (colored blue). Node sizes scale proportional to total degree centrality, with larger nodes indicating more connections. Edge thickness corresponds to transmission strength measured by F-statistic magnitude, with thicker arrows indicating stronger causal relationships. Edge colors transition from light gray for weaker pathways to dark black for the strongest transmission channels. The layout employs a force-directed positioning algorithm that places nodes with higher connectivity closer together. Financial sector nodes cluster centrally due to their high connectivity, whereas peripheral sectors such as utilities and consumer staples occupy peripheral positions. Directional arrows point from causally prior to causally subsequent variables, enabling visual identification of predominant transmission directions. Labels accompany each node, indicating the market segment name, while edge labels display average transmission lag in days. A legend in the lower right corner explains node shapes, colors, and size scaling, while a separate edge legend shows the F-statistic magnitude ranges corresponding to different thickness levels.

4.3. Transmission Intensity Quantification

Table 5: Volatility Spillover Indices Across Crisis Episodes

Time Period	Credit→Equity Spillover	Equity→Credit Spillover	Total Connectivity	Spillover Asymmetry
Normal (2010 - 2019)	23.4%	18.7%	42.1%	1.25
2008 Crisis Peak	**81.2%**	**54.3%**	**135.5%**	**1.50**
2008 Crisis Overall	67.9%	47.8%	115.7%	1.42
2020 COVID Peak	73.6%	51.2%	124.8%	1.44
2020 COVID Overall	62.4%	44.9%	107.3%	1.39
2023 Banking Peak	68.9%	48.7%	117.6%	1.41
2023 Banking Overall	58.3%	42.1%	100.4%	1.38
All Stress Periods Avg	62.9%	44.9%	107.8%	1.40

Note: Total Connectivity is defined as the sum of directional spillovers (Credit→Equity + Equity→Credit), so values may exceed 100%.

Volatility spillover analysis based on forecast error variance decomposition quantifies the percentage of each market segment's forecast uncertainty attributable to shocks in other segments. During normal periods, credit markets explain 23.4% of equity market volatility on average, while equity markets account for 18.7% of credit market volatility. This baseline 42.1% total connectivity reflects moderate interdependence under tranquil conditions.

Table 6: Sector-Specific Transmission Strength Rankings

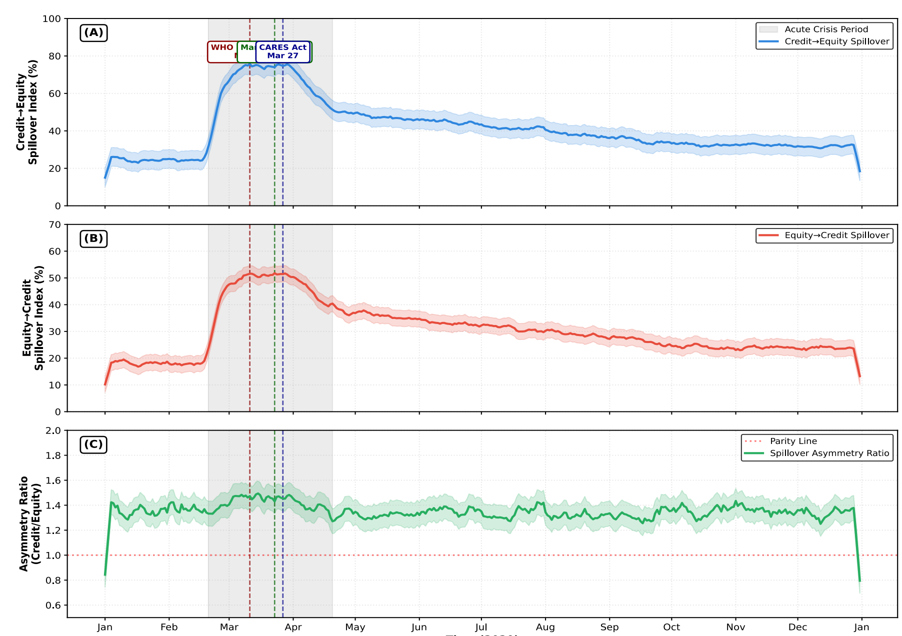
Equity Sector	Credit→Equity Strength	Rank	Equity→Credit Strength	Rank	Combined Score	Overall Rank
Financials	**0.89**	1	**0.73**	1	**1.62**	1
Energy	0.76	2	0.61	3	1.37	2
Industrials	0.72	3	0.58	4	1.30	3
Technology	0.68	4	0.54	5	1.22	4
Materials	0.65	5	0.52	6	1.17	5
Consumer Discretionary	0.63	6	0.49	7	1.12	6
Real Estate	0.59	7	0.64	2	1.23	7
Communication Services	0.56	8	0.46	8	1.02	8
Health Care	0.51	9	0.42	9	0.93	9
Consumer Staples	0.48	10	0.39	10	0.87	10
Utilities	0.44	11	0.36	11	0.80	11

Transmission strength rankings employ composite measures combining Granger causality F-statistics, correlation changes, and spillover index contributions. The financial sector demonstrates overwhelming dominance with a combined score of 1.62, substantially exceeding the second-ranked energy at 1.37.

Table 7: Dynamic Contagion Metrics by Crisis Phase

Crisis Phase	Average Network Density	Spillover Index	Betweenness Centrality (Financials)	Peak Correlation	Recovery Time (Days)
2008 Pre - Crisis	0.28	32.1%	0.35	0.42	-
2008 Acute Phase	**0.71**	**82.7%**	**0.61**	**0.87**	-
2008 Recovery	0.43	51.2%	0.44	0.58	187
2020 Pre - Crisis	0.24	28.4%	0.32	0.39	-
2020 Acute Phase	0.64	75.3%	0.57	0.81	-
2020 Recovery	0.38	46.8%	0.41	0.53	94
2023 Pre - Crisis	0.25	29.7%	0.33	0.41	-
2023 Acute Phase	0.58	69.4%	0.52	0.76	-
2023 Recovery	0.34	42.1%	0.38	0.49	67

Figure 4: Time-Varying Transmission Strength Through 2020 COVID Crisis



This figure displays three stacked time series panels covering January 2020 through December 2020 at a daily frequency. The top panel plots the credit-to-equity spillover index as a solid blue line with values on the left y-axis ranging from 0% to 100%. The middle panel shows the equity-to-credit spillover index as a solid red line using the same scale. The bottom panel presents the spillover asymmetry ratio (credit/equity) as a green line, with a right-hand y-axis ranging from 0.5 to 2.0. All panels share the common x-axis displaying calendar months. Vertical gray-shaded regions indicate the acute crisis period from February 20 to April 20, 2020, encompassing the initial market collapse and early recovery phases. Additional vertical dashed lines indicate key events, including the WHO pandemic declaration (March 11), the market bottom (March 23), and the passage of the CARES Act (March 27). The credit-to-equity spillover surges from 25% in January to a peak of 75% in mid-March, then declines gradually to 45% by June and stabilizes around 35% through year-end. Equity-to-credit spillover displays parallel but smaller-magnitude movements, rising from 18% to 52% at its peak and declining to 32% by December. The asymmetry ratio spikes above 1.5 on peak crisis days, indicating intensification of credit market dominance, before reverting to a baseline of 1.2 during the recovery. Smooth lines employ 7-day moving averages to reduce noise, while confidence bands show 95% intervals from bootstrap estimation.

5. Conclusions and Policy Implications

5.1. Key Research Findings Summary

The empirical analysis reveals several critical insights regarding risk contagion pathways between U.S. credit and equity markets during stress periods. Network topology transitions exhibit consistent patterns across multiple crisis episodes, with correlation density increasing by approximately 165% and causality density increasing by 150% relative to normal periods. These structural shifts indicate a systematic movement toward greater market integration during stress, supporting concerns that diversification benefits are reduced when they are most valuable. The topology changes occur rapidly following crisis onset, typically reaching peak connectivity within 2-4 weeks of the initial manifestation of stress.

Financial-sector equity emerges as the dominant transmission channel linking credit-market disruptions to broader equity-market weakness. The sector exhibits the highest centrality measures across multiple network metrics, functions as the strongest predictive pathway for credit-to-equity transmission, and demonstrates the tightest temporal coupling with 1–2-day lags. This centrality reflects financial institutions' unique position: they simultaneously participate in credit markets as borrowers and intermediaries and serve as equity market components. Policy frameworks emphasizing financial sector resilience are supported by empirical evidence documenting the sector's importance in transmission.

Transmission intensity quantification reveals that credit markets exert a stronger influence on equity markets than the reverse during all analyzed stress periods. The consistent 1.38-1.50 spillover asymmetry ratios indicate that credit market shocks explain 38-50% more equity market volatility than equity shocks explain credit market volatility. This directional dominance suggests credit market developments provide leading indicators for subsequent equity market adjustments. The magnitudes of asymmetry increase during acute crisis peaks, reaching maximum values around pivotal events such as the Lehman Brothers bankruptcy and the COVID-19 market bottoms.

Cross-crisis comparisons identify both common patterns and episode-specific variations in contagion dynamics. All three analyzed stress periods share qualitative features, including topological densification, financial-sector centrality, and informational leadership in credit markets. The 2008 financial crisis consistently exhibits the highest magnitudes across metrics, reflecting its origins in banking systems and associated credit-market disruptions. The COVID crisis displays the most rapid initial intensification due to its sudden exogenous shock character, though peak magnitudes remain below 2008 levels. The 2023 regional banking stress exhibits more concentrated impacts on financial-sector pathways, with narrower spillovers to other sectors.

5.2. Policy Recommendations for Financial Stability Monitoring

The identified contagion pathways suggest several policy applications for financial stability monitoring frameworks. Network density metrics calculated using rolling 60-day windows provide real-time indicators of trends in interconnectedness. Sustained density increases above 0.45 for correlation networks or 0.35 for causality networks could trigger enhanced supervisory attention and targeted data collection. These threshold levels correspond to the midpoints between normal and crisis-period averages, providing early warning before full crisis intensification occurs. Automated monitoring systems could generate alerts when density crosses thresholds or displays accelerating growth patterns.

Financial sector centrality measures warrant particular surveillance attention given empirical evidence of the sector's transmission dominance. Monthly calculations of financial sector betweenness centrality, degree centrality, and eigenvector centrality establish baseline distributions during normal periods. Deviations exceeding two standard deviations from the normal range indicate abnormal financial sector connectivity and warrant investigation. The specific banks or financial institutions that drive increases in aggregate centrality become focal points for deeper examination of potential systemic vulnerabilities. This sector-specific monitoring complements traditional microprudential supervision by focusing on individual institutions' soundness.

Granger causality testing between credit and equity markets provides lead-lag relationship intelligence valuable for stress testing scenario design. The documented 1–4-day transmission lags from credit to equity markets suggest credit market stress indicators offer short-term predictive content for subsequent equity market movements. Stress-testing scenarios that incorporate sequential shock propagation through identified pathways yield more realistic loss estimates than scenarios that assume simultaneous shocks across all markets. The pathway-specific transmission lags inform realistic timing assumptions for cascade development in stress-testing narratives.

Volatility spillover indices aggregated at weekly or monthly frequencies track overall system integration levels. Spillover values exceeding 60% for the credit-to-equity transmission signal were associated with elevated contagion risk. The combination of high spillover magnitudes with rising network density provides stronger warning signals than either metric in isolation. Regulatory authorities could establish graduated response protocols, with information gathering at 50% spillover thresholds, enhanced reporting requirements at 60%, and potential supervisory actions at 70% if sustained over multi-week periods. These graduated responses balance the benefits of early intervention against the risks of false positives from temporary spillover spikes.

The sector-specific transmission rankings inform the allocation of risk-based supervision. Beyond the financial sector's obvious importance, the energy sector's second-rank position warrants closer monitoring of energy firms' credit conditions and equity market performance. Credit exposures to energy companies warrant scrutiny, particularly during episodes of oil price volatility that affect the sector's debt-servicing capacity. Similarly, the real estate sector's elevated equity-to-credit transmission strength justifies continued attention to property market indicators as potential harbingers of credit stress.

5.3. Research Limitations and Future Directions

Several methodological limitations merit acknowledgment. The analysis focuses exclusively on publicly traded equity markets, potentially missing over-the-counter credit market dynamics and private credit transmission channels. Corporate bond markets, bank loan markets, and private credit funds constitute substantial credit market segments that interact with the public equity and CDS markets analyzed here. Future research that incorporates broader coverage of the credit market would yield more comprehensive contagion mapping. The technical challenge involves obtaining high-frequency private-market data comparable to publicly available equity and CDS data.

The network construction approaches employed here represent two among numerous possible methodologies. Alternative network definitions based on mutual information, transfer entropy, or tail dependence copulas might reveal complementary transmission patterns. Nonlinear causality testing addresses potential limitations of linear Granger causality in capturing threshold effects or regime-switching behaviors. Systematically comparing multiple network construction methods would establish the robustness of the identified pathways across specification choices. Such comparative analysis requires substantial computational resources, given the numerous series and rolling estimation requirements.

The identification of stress periods relies on objective statistical thresholds but inevitably involves some subjectivity in crisis demarcation. Alternative identification schemes employing NBER recession dating, CBOE stress indices, or narrative approaches may yield different definitions of crisis periods. Sensitivity analysis of stress-period windows would quantify how pathway identification and strength estimation depend on precise crisis dating. Preliminary analysis suggests that the main findings remain robust to moderate variations in timing, but comprehensive sensitivity testing awaits further investigation.

Geographic scope limitations restrict findings to U.S. markets, though contagion inherently involves cross-border transmission. Extending the analysis to international markets and examining U.S. linkages with European and Asian financial systems would address this limitation. The methodological framework developed here can be applied directly to international settings, given data availability. Key questions concern whether U.S. market dominance primarily entails outward transmission or whether bidirectional spillovers operate across developed markets. Emerging market linkages to U.S. credit and equity markets present additional research opportunities with important policy implications.

Temporal coverage ending in December 2024 excludes future crisis episodes that will inevitably provide additional natural experiments. Periodic updates to this analysis as new stress periods emerge will test whether the identified patterns persist or evolve as market structures change. Machine learning applications that aggregate multi-crisis data may enable the prediction of pathway-specific contagion intensities from crisis characteristics. Such predictive models would enhance real-time monitoring by forecasting likely transmission channels based on observed initial manifestations of stress.

References

[1]. Apostolakis, G., & Papadopoulos, A. P. (2024). Quantifying the volatility spillover dynamics between financial stress and US financial sectors: Evidence from QVAR connectedness. International Review of Financial Analysis, 95, 103661.

[2]. Battiston, S., Caldarelli, G., May, R. M., Roukny, T., & Stiglitz, J. E. (2018). Financial networks and stress testing: Challenges and new research avenues for systemic risk analysis and financial stability

implications. Journal of Financial Stability, 35, 159-171.

[3]. Chen, X., & Liu, Q. (2008). Financial contagion analysis based on hybrid nonlinear mutual prediction algorithm and fuzzy neural networks. In 2008 4th International Conference on Wireless Communications, Networking and Mobile Computing (pp. 1-4). IEEE.

[4]. Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. Economic Journal, 119(534), 158-171.

[5]. Elsinger, H., Lehar, A., & Summer, M. (2006). Systemic risk monitor: A model for systemic risk analysis and stress testing of banking systems. Financial Stability Report, 11, 83-95.

[6]. Huang, X., Vodenska, I., Havlin, S., & Stanley, H. E. (2021). Systemic stress test model for shared portfolio networks. Scientific Reports, 11, 3513.

[7]. Leung, H., Schiereck, D., & Schroeder, F. (2017). Volatility spillovers and determinants of contagion: Exchange rate and equity markets during crises. Economic Modelling, 61, 169-180.

[8]. Li, W., Chen, X., Zheng, Q., & Zhang, Y. (2023). Market volatility spillover, network diffusion, and financial systemic risk management: Financial modeling and empirical study. Mathematics, 11(6), 1396.

[9]. Liu, Y., & Zhang, X. (2011). Global contagion of the U.S. financial crisis: An exploratory spatial data analysis. In 2011 International Conference on Management and Service Science (pp. 1-4). IEEE.

[10]. McIver, R. P., & Kang, S. H. (2024). Analyzing risk contagion and volatility spillover across multi-market capital flow using EVT theory and C-vine copula. PLoS ONE, 19(11), e0313211.

[11]. Rogers, L. C. G., & Veraart, L. A. M. (2013). Failure and rescue in an interbank network. Management Science, 59(4), 882-898.

[12]. Tang, Y., Xiong, J. J., Luo, Y., & Zhang, Y. (2019). How do the global stock markets influence one another? Evidence from finance big data and Granger causality directed network. International Journal of Electronic Commerce, 23(1), 85-109.

[13]. Vodenska, I., Aoyama, H., Becker, A. P., Fujiwara, Y., Iyetomi, H., & Lungu, E. (2022). An integrated macroprudential stress test of bank liquidity and solvency. Journal of Financial Stability, 60, 100803.

[14]. Wang, J., Chen, R., & Li, M. (2017). Study on risk spillover effects of shadow banks on traditional banks in China. In 2017 4th International Conference on Industrial Economics System and Industrial Security Engineering (pp. 1-5). IEEE.

[15]. Zhang, M., & Wu, H. (2010). Empirical analysis on contagion effect of international financial crisis based on VAR model. In 2010 International Conference on E-Product E-Service and E-Entertainment (pp. 1-4). IEEE.